

Technical efficiency of the generation of knowledge in the European Union (2003-2010)

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Abstract. This paper analyses the determinants of knowledge in the European Union of the 27, through estimates of transcendental logarithmic production functions (translog) in different scenarios. For this, a data panel for the period 2003-2010 has been elaborated, selecting the production stochastic frontier as the most reliable model to estimate technical efficiency for European innovation. The empirical result is that technological capital, human capital and relational capital have a positive and significant influence on the generation of knowledge. Also, from the observation of results we can assure that the size (in terms of population) of a country within the EU-27 does not positively influence the technical efficiency of knowledge production.

This is an empirical study about the relationship between the determinants of knowledge and the technical efficiency of the generation of knowledge, and such a study does not exist in literature for the EU-27 in the period analysed.

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Contents:

1. Introduction	8
2. Literature review	8
3. Theoretical framework of the model and the analysis of technical efficiency in knowledge	10
3.1. Model	10
3.2. Stochastic frontier of technical efficiency in European knowledge	11
4. Variables and data used	12
5. Results	13
6. Conclusions	15
References	15

1. Introduction

In the innovative process developed within the countries of the European Union today, the possibility that technical efficiency of such knowledge activities differs among the set of countries studied will be considered. The result will be a modelling of the knowledge production strong enough to assess which countries are leaders in the use of inputs to generate knowledge, and which ones should consider modifying their innovative strategy. This strategy is basically defined by the combination of those inputs which, together, generate knowledge, such as technological capital, human capital and collaborative factors among enterprises and institutions, which, we assume, a priori facilitate knowledge production in each country. This is defined as relational capital. The starting point will be a data panel obtained from the *European Innovation Scoreboard*, an annual report published by the European Commission since 2003 inclusive, for all 27 countries in the European Union.

In general, there are different points of view that attempt to address the issue of efficiency. However, this concept is so complex that it has been broken down by economic theory into two components, the orthogonal multiplication of which results in economic efficiency. The first one, called allocative efficiency, attempts to find out to what extent inputs are hired more or less efficiently; in other words, paying competitive prices. On the other hand, the second component of economic efficiency is called technical efficiency, and is defined as output maximisation, considering specific amounts of inputs and a specific technology or combined form of such inputs.

The present study will focus on quantifying the degree of technical efficiency of each country when compared to the rest, so as to rank them and show which countries maximise technical efficiency in generating knowledge, considering the inputs they possess.

The structure of this paper is as follows: the next section will present a brief literature review, the third section will address the theoretical framework using one estimation methodology: stochastic production frontiers, to be reviewed in the third section and specified in the theoretical model as translog pro-

duction functions. The data and the variables used in the model will be presented in the fourth section. Next, the econometric results obtained will be assessed and, finally, a number of conclusions will be presented.

2. Literature review

The issue of technical efficiency has been raised in recent decades by numerous authors, acquiring particular significance when applied to the estimation of aggregate production functions. Thus, most works in this field have focused on the study of technical efficiency in the generation of added value and total factor productivity.

First, Afriat (1972) analysed the main studies published previously on the analysis of technical efficiency of the added value production functions. He stated –as a criticism– that econometric estimation techniques were remarkably simple and predictable, in most cases maintaining the classical regression model. Thus, he elaborated an extension of that theoretical model, introducing into the production function the possible existence of inefficiencies in the production process, including an error term containing two components: one which was fixed and one which could oscillate. This term adopted an exponential form, assuming that its density was distributed on the basis of the known gamma density function. In the same work, he proposed the econometric estimation method of maximum likelihood.

Subsequently, Aigner et al. (1977) also made interesting contributions to the field of empirical estimation of technical efficiency collected in the various functional forms that production functions can adopt. As Afriat (1972), they placed the initial reference of technical efficiency consideration in the context of applied economic analysis, in the work of Farrell (1957). However, the innovation of these authors lay in presenting an estimate of a stochastic production function, whereas previous work had focused on analyses based on a deterministic production frontier, although, as we shall see, this last method has continued being used. Within empirical contrasts, numerous production frontier models are used which show that estimates of the stochas-

tic frontier are not substantially different from those known so far, although maximum likelihood values point to a better approximation of technical efficiency using stochastic production frontiers.

Meanwhile, Meeusen et al. (1977) analysed technical efficiency in the French manufacturing sector in 1962, and produced a ranking of the existing technical efficiency in all productive sectors of the time, analysing this concept and considering most of the methodologies for estimating technical efficiency proposed so far. Their main result showed that the most efficient production sectors were those of footwear, sugar and drinks, whereas the group of industries leading inefficiency included the glass industry and dairy products.

Greene (1980), inspired by the idea of Aigner et al. (1968), also proposed an econometric model for the purpose of correcting the intercept of a regression estimated in the first stage, to then compare estimates of the dependent variable with their true values, excluding that common intercept. To this end, he developed a deterministic production frontier model, and obtained an indicator of technical efficiency in the production of the U.S. metallurgical sector.

A great contribution to the specification of technical inefficiency was made by Schmidt et al. (1984), who studied inefficiency considering a production function within the U.S. airline industry, using the data panel methodology for a period spanning from 1970 to 1978 and studying different airline data quarterly during those eight years. Furthermore, they proposed a novel specification of the common intercept, within the estimate of stochastic production functions frontiers, which consisted in assigning a binary variable for each of the airlines, thus collecting the individual effect that each of them had on the efficiency of the sector as a whole. On the other hand, they included the random disturbance component, variable for each company and each moment. Similarly, Battese et al. (1992 and 1995) continued to examine technical efficiency in the production function for agricultural enterprises in India, and also considered the stochastic production frontier, finding that the companies considered hardly varied their efficiency over time, so the component associated with each particular company was statistically irrelevant; that is, changes in technology occurring throughout the

study period did not result in an increase in technical efficiency.

Furthermore, Baños-Pino et al. (1999) and Coto-Millán et al. (2000) conducted various estimates of allocative and economic efficiency, respectively, within the port and airport transport industry in Spain, verifying that deterministic and stochastic parametric methods differed in their results.

More recently, Pires et al. (2004) found, with a panel of 35 developed countries in the period 1970–2000, that the main part of the observed technical progress was explained by the good performance of technical efficiency, despite the fact that allocative efficiency suffered a moderate decline. They also concluded that a part of technological progress was not entirely explained by efficiency, even after incorporating technological expenditures in innovation.

Alvarez et al. (2007) focused their analysis on the evolution of economic efficiency in the dairy sector in the province of Asturias, estimating the corresponding costs function. They showed that extensive production was less costly than intensive production in terms of the inputs used, but more inefficient in terms of technical efficiency.

Andrés et al. (2010) conducted one of the most recent works dealing with technical efficiency, estimating stochastic frontiers for coffee production in Colombia. They sectioned the sector by the supply side, and found that the most efficient coffee farms were those which were larger in size (with efficient coffee production levels around 90%), whilst small and medium farms barely reached 70% technical efficiency. Coto-Millán et al. (2007) analysed the technical and economic efficiency of Spanish airports for the period 1992–1994. Rodríguez et al. (2007) studied technical efficiency in ports. Furthermore, Tapiador et al. (2008) and Lozano et al. (2011) analysed technical efficiency for airports in 2006 and 2007, respectively. Size is important in the results of many empirical studies for airports, ports and other sectors: economies of scale are achieved and larger production units are more technically efficient.

Therefore this research will study whether the size of a country (in terms of population) generates more technical efficiency or not.

With respect to the specific literature review on the estimation of knowledge production functions, the background is found in Griliches (1979), who pointed out that the main determinants of

knowledge production (measured by the number of innovation patents) are the expenditure in R&D (hereinafter referred to as technological capital) and the Human Capital. Authors such as Jaffe (1986) added other important variables to the production function in order to capture effects of proximity dimensions on knowledge spillovers. The work of Jaffe (1989) attempting to measure the real effect of academic research is also of great interest. These works have inspired the following investigations: Coto-Millán et al. (2011), estimating technical efficiency in the production of innovation in the Atlantic Arc regions for 2002–2006, Badiola and Coto (2012), analysing an innovation production function for European regions for the period 2002–2006, Badiola et al. (2012), analysing the determinants of technical efficiency and innovation in the European regions during the period 2002–2006, and Agüeros et al. (2013), investigating the determinants of a knowledge production function for European countries during the period 2003–2009.

In particular, there is little literature on research works which adopt methodologies of knowledge production efficiency with regression models based on parametric and nonparametric approaches. It is worth mentioning the works by Moreuno et al. (2005) to capture the spillover effects in European regions and the investigations by Marrocu et al. (2011a) and Marrocu et al. (2011b) to capture the factors of proximity and density of social networks in the knowledge production function.

The work by Miguelez et al. (2013) estimates a knowledge production function for major European regions with panel data for the period 2000–2007, using the method of parametric frontiers. It concludes that knowledge generation is positively influenced by the traditional variables technological capital and human capital, and by labour mobility between regions, as well as negatively influenced by the density of social networks. In addition, the most technically efficient regions in the production of knowledge are concentrated in central Europe and Scandinavia. However, the highest production of knowledge occurs not only in regions belonging to Finland and Sweden, but also in regions of France, northern Italy, Germany, Spain, Denmark, Austria and the Netherlands. It is noteworthy that some regions in these countries are highly specialised in the manufacturing sector, such as Emil-

ia-Romagna, Lombardy, Veneto and Piemonte in Italy, Rhône-Alpes in France and Stuttgart in Germany. There is also a “proximity to a big city” effect that is highly important so that regions where major cities are located, such as Stockholm, Île de France, Catalonia, Düsseldorf, Vienna, Berlin, Lazio, Köln, Madrid and Hanover, are more efficient in producing knowledge.

Finally, the work of Fodi et al. (2013) estimates the knowledge production function in key European regions with panel data for the period 2000–2007, using the two methods of parametric and nonparametric frontiers, concluding in both cases that regions located in central Europe, such as Île de France, Stuttgart or Belgian Noord-Brabant, are the most efficient, while more peripheral regions are the least efficient, in particular regions of countries which have joined the European Union most recently.

3. Theoretical framework of the model and the analysis of technical efficiency in knowledge

3.1. Model

In this section the theoretical framework of the knowledge production function is presented, for which we adopt an empirical econometric specification.

Following the economic literature on the estimation of knowledge production functions (Griliches, 1979; Jaffe, 1986, 1989; Cohen et al., 1990), as determinants of the knowledge activity we include the human capital and the expenditures in R&D (technological capital). Also, the econometric specification of the model proposed in this research includes another variable, determining the generation of knowledge, which we will call relational capital. This includes the collaborative capacity among institutions and businesses, and is measured from the number of innovative and knowledge-generating research projects developed by private companies in collaboration with other private companies or by private companies in collaboration with public and/or private institutions. This new variable is inspired by the work of Ponds et al. (2010).

Next, the analytical process described in the introduction section will be developed, stating the necessary equations that lead to the analysis of the object of study. The first consideration to keep in mind is that efficiency analysis can be approached from two perspectives: the first one is to use non-parametric estimation tools (particularly Data Envelopment Analysis or DEA) and the second one is to use parametric tools. In the latter case, the most common techniques are those focused on estimating parametric stochastic production frontiers.

3.2. Stochastic frontier of technical efficiency in European knowledge

In order to analyse in depth the issue of technical efficiency in the knowledge of European Union countries, we will consider a model of stochastic production frontiers, as opposed to the deterministic analysis of technical efficiency.

Firstly, Wold (1938) developed the theorem used by all the econometric foundations of this model in the field of time series. He established that every variable to be explained could always be divided into two processes; a deterministic one, which does not vary over time, and a stochastic one, appearing as the result of the imperfection regression considered, which will decrease proportionally to the level of description of the dependent variable (innovation, in this case). Subsequently, the works of Aigner et al. (1977) and Meussen et al. (1977) considered that the production process is subject to two different types of random perturbations: a vector of intercepts, invariant over time, for each of the cross-sectional units (countries, in this case), and

a random component, which varies according to each country and in each time period.

The first vector contains the random effects that can be registered in production and are not under the control of the decision unit, but are inherent to the country, while the second vector includes purely stochastic factors, which are not observable in our model. Since the first component of the error term includes the specific individual effects of each production unit, depending on these individual effects being correlated or not with the observable explanatory variables, it is possible to apply two types of estimation models with panel data: the fixed effects model (in the first case) or the random effects model (in the second case).

In order to develop the process of econometric estimation of the stochastic frontier, the starting point will be equation (a).

$$y_{it} = f(x_{it}, \beta) e^{-v_{it}} \quad (a)$$

Where $e^{-v_{it}}$ represents the entirety of random disturbance, and which in turn, can be decomposed in expression (b).

$$e^{-v_{it}} = e^{-\left(\psi_{it} + \sum_{i=1}^{25} D_i\right)} \quad (b)$$

At the same time, we will assume that ψ_{it} is a random disturbance that satisfies the hypothesis of white noise described by the Gauss-Markov theorem.

Finally, it should be noted that the stochastic production frontier will also be considered based on the translog functional form. Therefore, the equation form to be estimated will be, in this case, equation (c).

$$\begin{aligned} \ln I_{it} = & \alpha_0 + \beta_1 (\ln K_{it} - \ln \bar{K}_i) + \beta_2 (\ln H_{it} - \ln \bar{H}_i) + \beta_3 (\ln R_{it} - \ln \bar{R}_i) + \\ & + \frac{1}{2} \gamma_1 (\ln K_{it} - \ln \bar{K}_i)^2 + \frac{1}{2} \gamma_2 (\ln H_{it} - \ln \bar{H}_i)^2 + \frac{1}{2} \gamma_3 (\ln R_{it} - \ln \bar{R}_i)^2 + \\ & + \gamma_{11} (\ln K_{it} - \ln \bar{K}_i) (\ln H_{it} - \ln \bar{H}_i) + \gamma_{12} (\ln K_{it} - \ln \bar{K}_i) (\ln R_{it} - \ln \bar{R}_i) + \\ & + \gamma_{11} (\ln H_{it} - \ln \bar{H}_i) (\ln R_{it} - \ln \bar{R}_i) - \psi_{it} - \lambda \sum_{i=1}^{25} D_i \end{aligned} \quad (c)$$

In this case, the regression will have a residue distributed into two components. The first component will be ψ_{it} , representing the random disturbance of the model and –we assume– adjusting to the hypothesis of white noise. A second component will be representing the technical inefficiency part of the model, estimated including twenty-five dummy variables, grouped in the summation of equation (c), $\lambda_i = \sum_{i=1}^{25} D_i$; where D_i will take the value 1 when, throughout the length of the panel, we refer to country “i”, and 0 in all other cases. These dummy variables will report on the influence that each country has on technical efficiency in the process of innovation production.

Thus, equation (d) defines the technical efficiency indicator for country “i”.

$$TE = e^{-\left(\psi_{it} + \lambda_i \sum_{i=1}^{25} D_i\right)} = \frac{1}{e^{-\left(\psi_{it} + \lambda_i \sum_{i=1}^{25} D_i\right)}} \quad (d)$$

Given the methodology composition of the indicator, it follows that technical efficiency will range from zero (absence of efficiency or maximum inefficiency) to one (maximum efficiency in the production of innovation). Technical efficiency will increase while estimates of the residual parameters which collect the individual effect of each country are significantly different from zero, to the extent that estimate λ_i tends to increase, and vice versa.

4. Variables and data used

In order to track innovation in Europe since 2001, the European Commission (2003, 2004, 2005, 2006, 2007, 2008, 2009 and 2010) decided to publish an annual report (European Innovation Scoreboard) with indicators on innovation, its determinants and economic effects. Thus, this organism issues annual reports with thirty indicators for each member, with the availability of data ranging from 2003 to 2010. These reports draw a comparison between the different EU countries to obtain basic information on the existing levels of innovation, creativity and technological progress in each country. For a more complete assessment of national competitiveness, a synthetic index of the fifteen-state European Union is included in the reports, which is then extended to the twenty-seven countries of the current European Union, and after that, to the thirty-two countries constituting geographical Europe. Thus, a study on the determinants of innovation in the area of the current European Union (27 countries) will be conducted, based on the different functional forms raised in the section devoted to developing the various theoretical models. We must also add that we lack much of the Maltese data for the set of indicators and years that make up the panel used, so this country has been excluded from the empirical analysis. Therefore, this article goes on to incorporate data from the remaining 26 countries of the European Union.

Each of the variables to be used in this investigation is methodologically broken down in Table 1. While, Table 2 presents the main statistics of the variables used.

Table 1. Structure of the indicators used

Indicator	Definition	Source (year)
Knowledge	Number of patents per million inhabitants annually recorded by the European Patent Office (EPO)	European Commission (2003 - 2010)
Technological capital	Average of the % of expenditure on R&D from public and private sectors in relation to each national Gross Domestic Product (GDP)	European Commission (2003 - 2010)
Human capital	Average between the % of graduates in the labour force and per thousand employed people who receive ongoing training at their workplace.	European Commission (2003 - 2010)
Relational capital	Average between the % of SMEs developing innovation with their own resources and the % of SMEs developing innovation in collaboration with other companies	European Commission (2003 - 2010)

Source: Own elaboration from the European Commission

Table 2. Main statistics of the variables used in the empirical analysis

	A		B	
	a	b	c	d
Mean	93.73	0.73	3.22	10.82
Median	32.80	0.63	16.10	19.85
Maximum	366.60	2.14	32.35	34.20
Minimum	0.70	0.14	3.25	5.85
SD	103.96	0.47	6.80	6.92
P-C	1.11	0.02	2.11	0.64

Explanation: A – output; B – input; a – knowledge; b – technological capital; c – human capital; D – relational capital

Source: Own elaboration

Table 2 shows the considerable relative variability existing within knowledge, measured by the Pearson coefficient. This variation is surpassed only by the human capital index. Secondly, it should be highlighted that the average value of the technological capital ratio is less than 1%, which was one of the targets set by the European Commission in 2010 when these reports began. Regarding relational capital, it is important to stress that it presents a moderate dispersion, with an average value closer to the minimum than to the maximum value of this indicator, which suggests that inter-enterprise collaborative activities are scarce throughout most of the European Union.

5. Results

The following lines present the results obtained from the estimation of the theoretical approach of technical efficiency analysis in the generation of knowledge considered previously.

Bearing in mind the theoretical content of section 3.2, an empirical study will be performed, estimating a translog production function, from the standpoint of technical efficiency with stochastic production frontiers.

Table 3 presents the results obtained from the theoretical approach of technical efficiency specified in equation (c).

Table 3. Econometric results of the estimation of the frontier of knowledge production

Estimations	Coefficient	t-ratio	
K	2.173	22.594	***
H	0.458	2.733	***
R	0.366	2.30	**
K ²	0.429	2.987	***
H ²	0.094	0.359	
R ²	0.767	2.639	***
K*H	-1.006	-2.60	**
K*R	-0.777	-3.038	***
H*R	-0.226	-0.652	
Trend	0.275	4.134	***
Trend ²	-0.034	-4.488	***
Statistics	N= 208		
F	338.46	p-Value = 0	***
R ² corrected	0.945		

Explanation: Symbols (*), (**) and (***) refer to the significance of the variables to 10%, 5% and 1% respectively

Source: Own elaboration

Firstly, from Table 3 it is worth mentioning that it includes the relatively high first order elasticities of the inputs to the output obtained; in this order, technological capital is the factor with the greatest influence on innovation, exceeding the unit (2.17). Next, we find that human capital occupies the second place, with a significantly lower elasticity (0.46) than that obtained for technological capital. Relational capital occupies the third position, with a smaller impact on innovation (0.37), although it is also a significant factor in explaining the behaviour of innovation.

The sign of the squared regressors will inform us of the marginal rate of return of each input. In the case of technological capital, it turns out to be significantly positive, so increased public and private expenditure on R&D will lead to increases in innovation at a higher rate, coinciding with the elasticity above one. The same applies to relational capital, whose quadratic estimate is positive and statistically significant.

Regarding the trend, we can say that it affects innovation positively, but must add that the square of the trend is significantly lower than zero. This means that the increase in innovation reaches a peak over time, after which the time trend will negatively affect the production of innovation.

Table 4 presents the estimates of the coefficients associated with the dummy variables corresponding to the translog innovation production function, according to the formulation of expression (c), ap-

plying the heteroskedasticity correction methodology of White (1980).

In Table 4 we see that the individual effect of each country in terms of knowledge is very different in every country.

Table 4. Individual contribution of each country to knowledge production

Country	Estimation		Country	Estimation	
Belgium	0.231	*	Lithuania	-3.554	***
Bulgaria	-3.456	***	Luxembourg	0.57	***
Czech Republic	-2.313	***	Hungary	-1.941	***
Denmark	0.705	***	Holland	0.687	***
Germany	0.865	***	Austria	0.372	***
Estonia	-2.351	***	Poland	-3.367	***
Ireland	-0.381	***	Portugal	-2.74	***
Spain	-1.392	***	Romania	-4.147	***
France	0.106	*	Slovenia	-1.06	***
Italy	-0.312	**	Slovakia	-2.615	***
Cyprus	-2.146	***	Finland	1.048	***
Latvia	-2.587	***	Sweden	1.006	***
Greece	-2.46	***	United Kingdom	0.20	**

Explanation: Symbols (*), (**) and (***) refer to the significance of the variables to 10%, 5% and 1% respectively

Source: Own elaboration

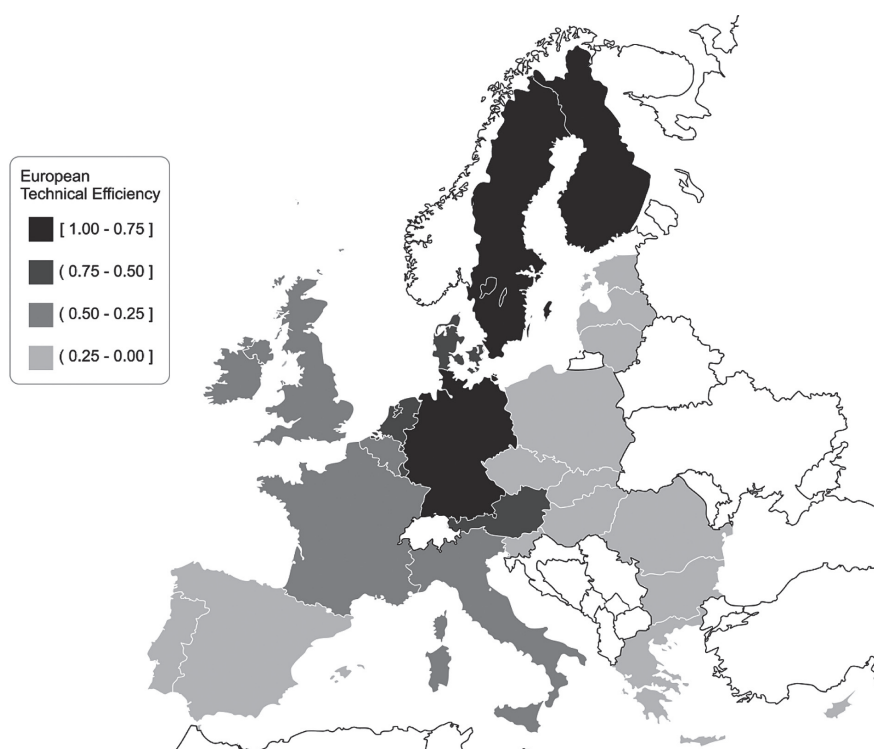


Fig. 1. European Technical Efficiency

Source: Own elaboration

Figure 1 illustrates the ranking of technical efficiency in European knowledge, estimated through the stochastic frontier considered in equation (c). The results ranking obtained with the stochastic frontier is led by Sweden, Finland, Germany, Holland, Luxembourg and Denmark, with all of them surpassing 70% technical efficiency. The UK, Slovenia, Spain and Hungary lie in the middle, and the classification is closed by Poland, Bulgaria, Lithuania and Romania, in that order.

6. Conclusions

From the survey conducted, we can conclude that it is important to analyse the composition and determinants of knowledge, as well as the degree of technical efficiency in generating such knowledge. Such studies of efficiency frontiers are widely present in the literature of various sectors, such as banking, airlines, ports, airports and agriculture, as noted in the literature review. Nevertheless, the literature on efficiency frontiers applied to knowledge production by European countries and regions is still very scarce.

With respect to the results, we found that the knowledge production functions yielded significant first order elasticities, with technological capital having the greatest importance in the function, human capital was second and relational capital had the least influence on production knowledge, although all three factors had a significant influence.

Furthermore, adding the estimates of the first order parameters of the inputs with respect to output, it follows that there are economies of scale in the production of knowledge.

Regarding technical efficiency of knowledge by countries, it is noteworthy that Sweden leads the technical efficiency ratio within the estimation method of stochastic production functions. Together with Sweden, countries such as Finland, Germany, Holland, Luxembourg and Denmark are at the forefront of efficient countries; while on the other hand, Romania, Lithuania, Bulgaria and Poland are among the least efficient.

From the observation of empirical results we can state that the size (in terms of population) of a country within the European Union of the 27 does not positively influence the technical efficiency of

knowledge production. In contrast, we can observe that those countries which have joined the EU-27 most recently present lower rates of technical efficiency in the production of knowledge.

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